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Online communities on competing platforms: Evidence from game wikis

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Abstract

Research Summary: Many platforms rely on volunteer contributions for value creation. Thus, unpaid contributors are valuable to the platform, but control over their activities is limited. We study *whether* and *how* volunteer communities can provide a competitive advantage and ask how contributor behavior depends on a platform's competitive position. We propose two channels: First, a stronger competitive position facilitates *contributor coordination*, leading to a larger active community. Second, a platform's competitive position is related to *contributor motivation*, which drives how much individuals contribute. Studying two competing game wiki platforms, we find that a platform's stronger competitive position is associated with higher activity, primarily driven by the number of contributors, which in turn triggers increased contributions by existing contributors. Further, high-productivity contributors are especially active on a stronger platform.

Managerial Summary: Online "crowdsourcing" communities create value for many digital platforms, but managing them in a way that ensures productive contributions is challenging. To better understand the conditions under which online communities create value productively we analyze how contribution patterns differ between more and less successful platforms. We study 13 game wiki communities on two competing platforms and find that success is tied to higher activity, which is in turn the result of more manpower in the value creation process, but also higher productivity by individual contributors. In addition, a dedicated core of highly productive community members is an important driver of platform success. These findings have implications for the motivation of community members, and the entry and growth strategies of crowdsourced platforms.

KEYWORDS

competitive advantage, digital platforms, online communities, platform competition, value creation

1 | INTRODUCTION

Value on digital platforms is often created by communities of volunteers contributing knowledge and skills for free (Fershtman & Gandal, 2011; Lakhani & Wolf, 2005; Lerner & Tirole, 2002). Such "crowdsourced" activities include providing knowledge on Wikipedia or creating tools and software on open source platforms like Github, but volunteer communities also contribute to product development (Shah, 2005; von Hippel, 1988), offer customer support (Shah & Nagle, 2020), enhance brand reputation (Muniz & O'Guinn, 2001), create content (Burtch, He, Hong, & Lee, 2020), and attract an audience which can be monetized via advertising (Evans, 2003). Scholars studying the sources of motivation for participation in such communities find that volunteers contribute because they enjoy the process (Jeppesen & Frederiksen, 2006) or if they see the need for a specific (software) solution (Osterloh & Rota, 2007; Shah, 2006). They care about the usefulness and impact of their contributions (Huberman, Romero, & Wu, 2009; Roberts, Hann, & Slaughter, 2006) and draw social benefits from collaborating (von Hippel & von Krogh, 2003; Zhang & Zhu, 2011).

Online communities can be a valuable resource for commercial platforms. However, their ability to control this resource is limited: Voluntary contributors choose if, when, and to what extent to participate in value creation. This autonomy may lead to levels and types of activities misaligned with platforms' expectations (Altman, Nagle, & Tushman, 2019; Kretschmer, Leiponen, Schilling, & Vasudeva, 2022; Nickerson, Wuebker, & Zenger, 2017). Hence, while volunteers can *potentially* create valuable output, it is uncertain that they actually do. The severity of these issues may be linked to a platform's competitive landscape. The presence and relative strength of rivals likely impact the size of a platform's online community, the audience it can reach, and—by extension—the nonpecuniary benefits contributors derive. Our understanding of how competition and contributor behavior interact is limited (Lerner & Tirole, 2002; von Krogh, Haefliger, Spaeth, & Wallin, 2012), and most studies on this relationship are theoretical (Athey & Ellison, 2014; Casadesus-Masanell & Halaburda, 2014; Llanes & de Elejalde, 2013; Sacks, 2015) or focus on competition that does not rely on volunteer contributions (Nagaraj & Piezunka, 2020). Hence, contribution dynamics in markets with competing platforms drawing from the same pool of potential volunteers remain largely unexplored.

We are interested in how communities of volunteer contributors form the basis of a platform's competitive advantage in terms of value creation. To that end, we investigate how contribution patterns differ conditional on the competitive position of crowdsourced platforms. Specifically, we ask two questions: First, *how does the activity and productivity of a platform's volunteer contributors depend on its competitive position?* And second, *which mechanisms tie macro-level platform competition to outcomes at the micro-level of contributors?*

Two key mechanisms connect a platform's competitive position to the activity and productivity of its contributors: First, *contributor coordination* affects the number of active contributors a community has at any time, the *extensive margin* of value creation. A stronger position is linked to a larger community, hence providing more manpower for collaborative output production. Beyond this size effect, we also consider *contributor motivation*, that is, if and how a stronger competitive position relates to contributors' ability to derive nonpecuniary benefits. This mechanism determines how active each contributor is, the *intensive margin* of value creation. Prior work on platform competition finds that a better position is tied to size (Caillaud & Jullien, 2003; Cennamo & Santalo, 2013). Common wisdom therefore is that *success breeds success* in that a dominant platform retains its position (Biglaiser & Crémer, 2016). By disentangling the extensive and intensive margins of contributor activity we go one step further and precisely identify *how* success is breeding success in the context of crowdsourced platforms.

We study two competing online platforms hosting video game wikis, *Fandom* and *Gamepedia*. As on Wikipedia, volunteers gather information and write articles about the content of different video games. We use contribution-level data to track value creation in these communities over time. Each platform hosts multiple wikis, each covering a different game and populated by different communities. Hence, some games are covered on one platform, others on both. This creates heterogeneity in their relative performance in output production across domains, which we use to operationalize a platform's competitive position. We use game updates as an exogenous impulse to contributor activity to establish a unidirectional causal link—we are interested in how activity varies by competitive position, not vice versa.

We provide four key insights: First, a stronger competitive position in a domain is related to higher aggregate activity, suggesting that *success breeds success* in the process of value creation. Second, this relationship is mainly driven by the *extensive margin*, that is, *more contributors* actively engage in collaborative value creation. Hence, more manpower is a driver of continued success. Third, there is a weak positive relationship between competitive position and activity at the *intensive* margin, that is, each contributor *contributes more* on a stronger platform. Consistent with direct network effects, we show that this relationship is likely due to higher social benefits derived from being part of a larger community. Finally, contributor heterogeneity matters: The activity of high-productivity contributors (HPCs) (top 10% in an online community) is positively related to a platform's competitive position, even after controlling for community size. This small subset of highly valuable contributors drives activity at the intensive margin to a large extent, making them an important aspect of a platform's advantage in value creation.

Our findings provide novel insights into the strategic management of crowdsourced platforms. The relative importance of the different elements of competitive advantage has important implications for the effectiveness of strategies aimed at platform growth and contributor motivation. Further, we show how differences in a platform's competitive position relate to nonpecuniary benefits that drive volunteer contributions. Hence, we provide insights into the relationship between the external and macro-level platform competition and sources of contributor motivation at the micro-level. Finally, the nuanced ways in which the competitive position interacts with contribution patterns of different contributor types suggest heterogeneity in the strength and relevance of both direct and indirect network effects.

2 | THEORETICAL BACKGROUND

2.1 | Online communities and user-generated content

2.1.1 | Online communities as firm resource

Many platforms organized around online communities rely on volunteer contributions to generate value (Kane & Ransbotham, 2016; Nagaraj & Piezunka, 2020). User communities feature in firms' innovation and product development processes (Antorini, Muñiz Jr, & Askildsen, 2012), either by providing novel design ideas (Shah & Tripsas, 2007) or by giving feedback on functionality (Goldman & Gabriel, 2005). They can contribute to firm reputation and brand loyalty by involving them in promotional campaigns (Antorini et al., 2012). Further, user communities provide product support (Shah & Nagle, 2020). The emergence of digital technologies facilitated the involvement of volunteer contributors and their commercialization. Many platforms focus their value proposition on user-generated content. For example, Yelp or TripAdvisor relies on user reviews (Zhu & Zhang, 2010) and maintain forums where they can exchange experiences. Similarly, Reddit hosts many communities whose members discuss various topics (Burtch et al., 2020). These platforms typically provide a technical infrastructure (e.g., a website and tool kits) while the user-generated content attracts viewers, which then generates advertising revenues. As a result, online communities often constitute a platform's most important resource.

However, online communities present platforms with nontrivial challenges: First, the pool of potential contributors may be limited (Shah & Nagle, 2020), and platforms may face competition in attracting them. Second, given its voluntary nature, firms have limited control over the types of activities contributors undertake (Altman et al., 2019; Nickerson et al., 2017). In fact, attempts at exercising control may put off contributors. Thus, the scope and types of contributions may not be fully aligned with the hosting platforms' needs. Hence, understanding the drivers of volunteer contributions is important to attract and deploy them successfully, and studying the interplay between inter-platform competition and volunteer behavior is key to understanding how their activities can give platforms a competitive advantage.

2.1.2 | Sources of contributor motivation

Work on contributors' motivation (Fershtman & Gandal, 2011; Lerner & Tirole, 2002; von Krogh et al., 2012) has identified a range of nonpecuniary benefits they can derive. Some may have a need for a particular solution themselves (Osterloh & Rota, 2007; Shah, 2006), they may participate in online communities to learn more about the content (Handley, Sturdy, Fincham, & Clark, 2006) or to work on a particular skill (Brabham, 2010; Lakhani & von Hippel, 2003). Others may simply participate as a hobby (Jeppesen & Frederiksen, 2006; Shah, 2006), because they enjoy the process (Lakhani & Wolf, 2005), or the autonomy associated with open source environments (Belenzon & Schankerman, 2015; Roberts et al., 2006).

Participation may also be driven by the impact their contributions have on others (Lerner & Tirole, 2002). Contributors consider the use value (Roberts et al., 2006; Shah, 2006) and accessibility (Fershtman & Gandal, 2007; Subramaniam, Sen, & Nelson, 2009) of the content they create and the audience they reach (Boudreau & Jeppesen, 2015; Goes, Lin, & Au Yeung, 2014;

Huberman et al., 2009; Qiu & Kumar, 2017). This can lead to a positive feedback loop of consumption and content creation (Kane & Ransbotham, 2016).

Social benefits can also be a source of motivation (Gallus, 2017; von Hippel & von Krogh, 2003). Contributors may enjoy collaborating with peers (Brabham, 2010; Zhang & Zhu, 2011), grow attached to the community (Ren et al., 2012; Ren, Kraut, & Kiesler, 2007) and develop a sense of identity and commitment (Bateman, Gray, & Butler, 2011; Chan & Li, 2010; Ma & Agarwal, 2007; von Hippel & von Krogh, 2003). Consequently, embeddedness in a network of peers can drive contributor activity (Gandal & Stettner, 2016; Shriver, Nair, & Hofstetter, 2013; Wasko & Faraj, 2005). Contributing can entail status-related benefits (Ariely, Bracha, & Meier, 2009; Roberts et al., 2006; Toubia & Stephen, 2013) and increase peer reputation (Archak, 2010; Belenzon & Schankerman, 2015). Hence, community-based awards and status-hierarchies can drive activity (Anderson, Huttenlocher, Kleinberg, & Leskovec, 2013; Burtch et al., 2020; Goes, Guo, & Lin, 2016; Restivo & Van De Rijt, 2012).

While these aspects are important *micro*-level antecedents to voluntary content creation, we know much less about how volunteer contributors are affected by platform competition, a *macro*-level construct, despite calls for more research (Lerner & Tirole, 2002; von Krogh et al., 2012). Prior work has been theoretical and analyzed the competition between open-source and commercial alternatives (Athey & Ellison, 2014; Casadesus-Masanell & Ghemawat, 2006; Llanes & de Elejalde, 2013; Sacks, 2015). In addition, Nagaraj and Piezunka (2020) empirically study how the level of contributor activity changed after entry by a commercial alternative. They find that on OpenStreetMaps, a community-driven platform, contributions by new members decreased after the entry of Google Maps, while established ones increased their contributions. We complement their findings by analyzing the impact of a platform's competitive position on contributor activity in the context of two entirely community-driven alternatives.

2.2 | Platform competitive position and contributor activity

We explore if and through which channels contributor activity varies by a platform's prior success. Specifically, the (past) content created by the community is the measure most closely linked to value creation and ultimately competitive advantage. Hence, we consider a platform's competitive position to be better if more content has been created on it in the past. Moreover, we disentangle mechanisms tied to its *relative* competitive position and its *absolute* community size, which lets us separate the channels through which the reinforcing success dynamics unfold in crowdsourced platform markets.

We argue that competitive position affects two distinct dimensions of contributor activity and value creation: First, it will affect the number of active contributors at any given time, that is, the *extensive margin* of value creation. Second, it will affect each active contributor's level of activity, or the *intensive margin* of value creation. Both dimensions together will determine the *aggregate* level of contributor activity.[1]

[1]Note that platform markets can tip toward a single player who does not face competition. Such "exclusive" platforms may present a special case. However, we expect our arguments about competitive position, community size, and the associated benefits to still hold. Moreover, the role and impact of the competitive position may also be maximized on exclusive platforms, as individuals contribute to the sole source of information. Therefore, we expect the same logic (laid out below) to apply.

2.2.1 | Contributor coordination and the extensive margin of contributor activity

Given the sizable network effects on community platforms, the value for the individual user is maximized if all adopt the same platform (Schilling, 2003; Zhu & Iansiti, 2012). Conversely, if a community of potential users is splintered across multiple disconnected networks, overall adoption and welfare is diminished unless users and networks are highly heterogeneous (Farrell & Saloner, 1986; Kretschmer, 2008; Simcoe & Watson, 2019).

When multiple platforms coexist, users face a nontrivial coordination problem: As they have to anticipate each others' adoption decisions, they cannot perfectly predict the value they will receive from joining one of multiple competing platforms (Halaburda & Yehezkel, 2016, 2019). Users then *coordinate* tacitly based on ex ante *beliefs* about which alternative is chosen by others (Caillaud & Jullien, 2001, 2003). Those beliefs are based on different signals such as the platforms' past ability to attract users (Argenziano & Gilboa, 2012; Biglaiser & Crémer, 2016) or other aspects of its track record (Halaburda & Yehezkel, 2019), such as the quality and quantity of the output produced by its members. Prospective adopters then expect the platform that has been more successful in the past to be their best option as well (Biglaiser, Calvano, & Crémer, 2019).

We expect similar dynamics in the competition between community-driven platforms. First, contributors generate output collaboratively, implying the existence of direct network effects. Aspects of the platform's past performance will drive (expected) utility from social benefits (Zhang & Zhu, 2011). Second, the number of people consuming the generated output is an important motivator for contributors (Boudreau & Jeppesen, 2015; Huberman et al., 2009), highlighting the role of indirect network effects. From a prospective adopter's point of view, a stronger competitive position in terms of the output created may then signal higher participation on the consumption side as well. Third, contributors may start out *consuming* the output before transitioning into a *contributing* role (Kane & Ransbotham, 2016; Nagaraj & Piezunka, 2020), giving a platform in a stronger competitive position an additional edge over its competitor(s). Together, a platform in a stronger competitive position will likely retain its position by attracting further contributors. Relatedly, a better performing platform is likely to exhibit a larger number of active contributors, that is, an advantage in terms of the *extensive margin* of value creation.[2]

2.2.2 | Contributor motivation and the intensive margin of contributor activity

Consider now the link between a platform's competitive position and the *intensive margin* of value creation, that is, the level of activity of each contributor on a platform. At the individual level, this link becomes a question of contributor motivation, that is, if and how the platform's competitive position is related to the (nonpecuniary) benefits they can derive from contributing.

Analogous to our logic in Section 2.2.1, a stronger competitive position is likely associated with a *larger* community. A greater size can have a direct impact on contributor behavior

[2]This effect should be maximized for exclusive platforms: Here, contributors do not have to coordinate on one of multiple alternatives.

through social benefits (Zhang & Zhu, 2011). In addition, it can foster a feeling of attachment and identity (Bateman et al., 2011; Ren et al., 2012, Ren et al., 2007) and enhance the quality of collaboration, dividing tasks among diverse contributors (Arazy, Nov, Patterson, & Yeo, 2011; Ransbotham & Kane, 2011). In addition, being part of a thriving community means that contributors can build on the work of others, enabling follow-on contributions (Aaltonen & Seiler, 2016; Gorbatai, 2014; Olivera, Goodman, & Tan, 2008). However, a larger community may also *decrease* the quality of collaboration as it may lead to conflict and increased coordination requirements (Arazy et al., 2011; Kittur & Kraut, 2008; Kittur, Suh, Pendleton, & Chi, 2007). These aspects describe how the competitive position is tied to contributor activity via community size.

Second, status-related motivation (Belenzon & Schankerman, 2015; Roberts et al., 2006) may also be related to a platform's competitive position. Conditional on occupying a position of high status in the community, a contributor's reputational benefits will likely be higher if the amount and quality of the aggregate output is higher—a direct link to the competitive position. Conversely, reaching a position of high status may be harder in a more active community, which implies that the marginal reputational benefit of contributing may be higher on a less successful platform. This is especially relevant if contribution opportunities are limited (Guo, Kim, Susarla, & Sambamurthy, 2020) and there is competition among contributors *within* a community (Boudreau & Jeppesen, 2015). Hence, this presents an indirect link to the competitive position again tied to community size. The relative strength of these two effects of the competitive position on contributor motivation can differ by the individual's ex ante status: high status contributors may draw further motivation from being on a strong platform, while low status individuals may find the intense competition among contributors on a strong platform discouraging.

Third, the competitive position should affect the motivation of *contributors* if it is associated with a large number of *consumers* of the generated output (Boudreau & Jeppesen, 2015; Subramaniam et al., 2009). If contributors care about the impact of their efforts (Lerner & Tirole, 2002), reaching a larger audience will lead to a greater feeling of accomplishment and ego-gratification (Huberman et al., 2009). For contributors who may not be able to observe consumption themselves, being part of the more productive platform may then signal an increased impact of their creation processes, driving subsequent participation. This type of benefit should be maximized when a platform is *not* facing a competitor. In that case, the community constitutes the exclusive source of information for the entire potential audience.

However, a strong competitive position can also have a direct impact over and above mere size. Facing a strong competitor may be motivating in itself. It can increase identification with the community (Hogg & Terry, 2000), which may encourage contributor effort. Contributors may also want to save their community from vanishing and preserve prior investments, especially if they contributed heavily in the past (Nagaraj & Piezunka, 2020). Hence, they may try to "out-compete" the other community through increased activity on a platform that is either in a worse competitive position than or on equal footing with the rival.

In sum, the relationship between a platform's competitive position and the *intensive margin* of value creation is ambiguous and may be subject to heterogeneity across contributors. Some motivational sources may be linked to differences in community size (e.g., social benefits), while others are linked to the competitive position more directly (e.g., status- or impact-related benefits). Empirically, we will separate the two to isolate the mechanisms through which the competitive position affects contributions.

2.2.3 | Heterogeneity across contributor types

Contributions to online communities typically follow a power law distribution (Rullani & Haefliger, 2013) where most content is produced by a small set of contributors (Gorbatai, 2014; Shah, 2006). These HPCs are experts in collective content production and are often involved in the online community as moderators and coordinators (Dahlander & O'Mahony, 2011). Less productive contributors operate at the periphery and contribute occasionally (Kriplean, Beschastnikh, & McDonald, 2008) and in specific areas (Shah, 2006). These groups may thus react to different motivations (Gorbatai, 2014; Kriplean et al., 2008; Panciera, Halfaker, & Terveen, 2009).

We expect status-related benefits to be especially motivating for HPCs. They create the majority of content, which creates a greater sense of "ownership" (Halfaker, Kittur, Kraut, & Riedl, 2009). Also, engaging in higher-level coordination activities (Dahlander & O'Mahony, 2011) gives them a sense of responsibility over the quality of the produced output, especially when they derive a sense of accomplishment through the consumption by the public (Boudreau & Jeppesen, 2015). In contrast, less productive contributors tend to build on existing output created by others (Aaltonen & Seiler, 2016; Olivera et al., 2008). Hence, HPCs may rely less on a large network of collaborating peers than less productive ones.

This difference in motivational sources has implications for the role of a platform's competitive position. First, as less productive contributors rely more on the presence of collaborators, we expect that the mechanisms that tie the competitive position to individual activity for them are connected to community size. On a more successful platform they encounter a larger network of peers opening up opportunities to build on the work of others. This may also increase their identification with a community. Second, while this type of social benefit may also motivate HPCs, they also tend to be driven by status- and impact-related benefits beyond mere size effects. Indeed, a more productive community may imply that they have to exert more effort coordinating the process of content creation, shifting their own activities from creating content to maintenance of existing content. This may demotivate less productive contributors, who are put off by excessive quality control (Halfaker, Geiger, Morgan, & Riedl, 2013). Overall, less productive contributors may be primarily driven by community size rather than the platform's competitive position per se. By contrast, for HPCs, being part of the community that produces more and higher-quality content should matter more, indicating an impact of a stronger competitive position beyond community-size effects.

3 | DATA AND METHODS

3.1 | Empirical setting

We study a platform's competitive position and contributor activity in the context of video game wikis. Similar to Wikipedia, contributors gather information about different video games—such as playable characters or levels—and compile them into publicly accessible articles.[3] Our dataset

[3]Figure A3 shows the article "Monsters" from the "Fortnite" wiki on Gamepedia.

contains information about the two most popular wiki-hosting platforms, Fandom and Gamepedia.[4] While Gamepedia only covers video games, Fandom hosts wikis about most forms of entertainment media. Gamepedia hosts more than 2000 game wiki communities, while Fandom has more than 385,000 wikis across all media types. Gamepedia and Fandom provide the digital infrastructure for many specialized, distinct wikis, started and maintained by users. They also provide support by way of standardized guidelines and staff who participate in the communities by contributing knowledge directly and/or providing maintenance (e.g., restoring articles affected by vandalism). The two platforms resemble Wikipedia[5] in structure and design. Both use the MediaWiki engine, the software used by Wikipedia. However, while Wikipedia is a unified repository for general knowledge, Gamepedia and Fandom host multiple disconnected wikis, each with specific information about a clearly defined domain, that is, the game it covers.

Although the content is licensed under Creative Commons, both platforms rely on advertising as their primary source of revenue. As such, they are "audience makers" (Evans, 2003) in the sense that they use wiki content to attract readers, which are subsequently monetized via advertising. Relying on volunteer contributors to attract an audience has important implications for the strategic tools at the platform's disposal. First, Fandom reports that 90% of traffic is generated via search engines, highlighting the importance of search engine optimization.[6] Interviews[7] with platform staff members confirm this, and some interviewees specifically mention the importance of having complete and high-quality content on their wikis. Both platforms employ community managers and other staff tasked with encouraging contributions by seeding wikis and articles about new features, offering support to volunteers, and structuring the wikis, or even creating content in areas where volunteer contributions are lacking. While search engine optimization (SEO) is mentioned as the primary goal of staff activities, hosting lively and self-sufficient communities is an integral part in achieving it. Hence, volunteer contributors are indeed the platform's primary resource, and gently "shepherding" contributors is one of the key tools available to the platform. Second, volunteer contributors themselves may thrive to out-compete the community covering the same game on the rival platform. Interviews with unpaid community members confirm that this indeed motivates some of them, especially highly engaged contributors. These insights suggest a virtuous cycle of adoption often observed in platform-based markets: The presence of content increases search engine performance, hence traffic. This seeds an audience and new contributors, which in turn improves the content. Hence, a platform's main way to get ahead is to enable and encourage volunteer contributions.

Video game wikis have features that make them well-suited for our research questions: First, we observe two platforms who offer virtually the same service and have to compete for

[4]www.fandom.com and www.gamepedia.com, respectively. Note that Fandom acquired Gamepedia's parent organization (Curse Media) from Twitch in early 2019. While there have been consolidation efforts since early 2020, this should not impact our analysis as our data collection concluded beforehand and covers earlier time spans. Still, developments leading up to this acquisition could affect the results of our analysis. For instance, Gamepedia becoming irrelevant relative to Fandom may have sparked the acquisition. However, we do not believe this to be the case for two reasons: First, because press coverage around the acquisition does not support this notion (e.g., D'Anastasio, 2018; Sutton, 2018), and second, to rule out such developments we re-ran our main analyses excluding the years 2018 and 2019, with consistent results.

[5]While Gamepedia clearly is playing on Wikipedia's name recognition, so was Fandom, which is also known as Wikia and primarily used this name before 2016.

[6]This information comes from a company blog post at https://community.fandom.com/wiki/User_blog:MisterWoodhouse/The_Future_of_Gamepedia [accessed: December 17, 2021].

[7]We conducted several semi-structured interviews to generate some qualitative insights about our empirical context. See Section A.7 in the Supporting Information for further information.

contributors and the value they create. Second, the platforms consist of multiple disconnected wikis, each covering a different video game, and each maintained by a different community. While some games are covered by only one platform, the majority is covered by both. Thus, the platforms are in competition for potential contributors in some (but not all) domains, and there exists considerable heterogeneity in each platform's competitive position. Third, the creators of the games we cover in our analysis regularly release content updates, providing an exogenous impulse to contributor activity, which we exploit in our identification strategy.

3.2 | Measuring competitive position

To measure competitive position, we exploit the fact that Gamepedia and Fandom host disconnected wiki communities covering different games. We observe the activity of each platform's contributors across these different domains. For three out of 13 domains (games), only one of the two platforms covered the game. For the other 10 games, contributors are distributed across the respective wiki communities on the two platforms, and we observe considerable heterogeneity in contributor activity, community size, and the output it creates over time, both within each platform and across games as well as across platforms and within each game. Hence, for some games contributors on Fandom create more output than Gamepedia or vice versa, and for others, the two are level with one another.

To measure a platform's competitive position within a domain we use the total number of articles in a wiki covering the respective game relative to the other platform. Articles contain information about the games, hence a larger number implies that more output has been created in the past, and that more content can be accessed by the public. With article count in a wiki, N, we calculate platform i's competitive position in domain g on day t as

$$\mathrm{CP}_{igt} = \frac{N_{igt}}{N_{igt} + N_{jgt}},$$

with subscript j indicating the other platform. This captures a platform's share ($0 \leq \mathrm{CP}_{igt} \leq 1$) of total articles written about a game over time, with larger values indicating a stronger competitive position. If $\mathrm{CP}_{igt} = 1$, platform i is the exclusive host of the entire community covering game g, that is, there only exist articles about it on that platform.[8]

Figure 1 illustrates the heterogeneity across different domains. Each panel shows the development of the platforms' competitive position in the coverage of a certain game over time.[9] In some domains, there is a dominant player throughout. For example, "Heroes of the Storm" is consistently covered more comprehensively on Fandom than on Gamepedia. We observe the opposite for "Hearthstone" or "Paladins", while for "Overwatch" or "Sea of Thieves" we observe more balanced competitive positions over time. The competitive position can also fluctuate significantly over time: For the game "For Honor", Gamepedia

[8]As a robustness check, we run our main analyses using two different measures of the competitive position. First, we use the total number of characters in a wiki as an alternative measure of cumulative community output. Second, we use a measure of community size (number of unique active contributors over the preceding 30 days) as the basis of a platform's competitive position. The results are robust to these alternative operationalization, and details are presented in Supporting Information Appendix A.2.

[9]We do not show the three games that are exclusively covered on one of the two platforms.

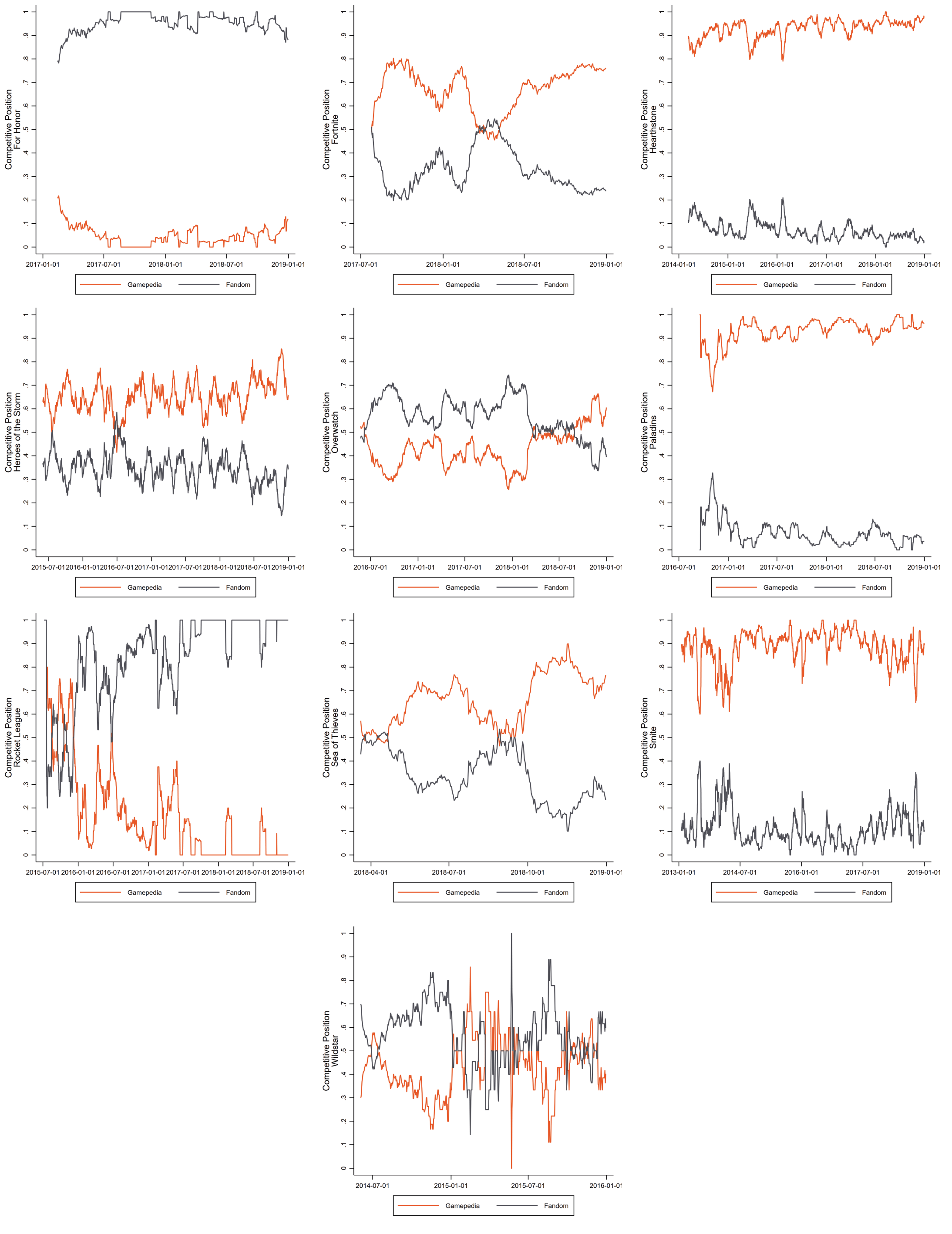

FIGURE 1 Development of the competitive position in different domains

started out in a leading position, which it subsequently lost to Fandom. Hence, neither of the two platforms is stronger across the board, and we observe variation in the competitive position even within domains.

3.3 | Identification strategy

Identifying the effect of a platform's competitive position on the activity of its contributors—and not vice versa—is an empirical challenge. In our setting, platform success depends on the content produced by a large, active community, as does its competitive position. Therefore, the causal link between the two likely works both ways, so that simply regressing one on the other would produce upward-biased estimates.

Absent random shocks to a platform's competitive position, we exploit updates to a game's content as an exogenous impulse to contributor activity. Our intuition is as follows: First, such updates trigger changes to a game's content, and often introduce new features such as characters, levels or game modes. As a result, contributors have to gather new information, write new articles, or revise existing ones to accommodate these changes (*impulse*). In addition, the decision to release an update is made by the game developer (i.e., the creator) and should not depend on the activity of contributors to wikis about the game, let alone the competitive position of the platforms hosting these communities (*exogeneity*). However, the timing of update releases may be related to the broader activity of the game's player base, which is likely related to the size of the active wiki communities. To address these concerns we use a rich set of time-varying fixed effects (see description below). Further, we run an analysis of the probability that an update is released as a function of the activity levels on the two platforms,[10] further alleviating the concern of endogenous update releases.

We use these exogenous updates in a quasi-experimental approach: We first hand-collected the release dates for all updates for the games in our sample. Game creators typically provide detailed information about the associated changes and new feature introductions. The majority of updates are "patches" that remove glitches or improve technical performance. As these do not change the game's contents, they should not induce activity to the wiki communities, and we do not use them in our analysis. For the remaining updates, we evaluate contributor activity in a narrow time window around the release date of each. Specifically, we use the 4 days before and the 5 days after and including this day. If release dates are close and would result in overlapping 9-day windows, we removed these updates. We use a total of 443 distinct updates across all games. Our research design resembles a regression discontinuity in time framework (RDiT, see Hausman and Rapson (2018)), similar to an event study design: Observations just after the release of an update are considered *treated*, those just before serve as *control*. As we observe multiple updates over time and across games, we estimate an average treatment effect (ATE) on different outcomes of interest. To explore the role of a platform's competitive position, we estimate heterogeneous treatment effects along this dimension. The idea behind our approach is that contributors to all wiki communities will increase their activity just after the release of an update, that is, we expect a positive ATE, but the effect size will depend on the competitive position. Hence, we estimate conditional average treatment effects (CATE).

We measure the competitive position 4 days before the release of an update and hold it constant over the entire 9-day window. This assumes that its perception by contributors does not change in those 9 days.[11] The competitive position around each update is thus not affected by the (expected) increase in contributor activity, mitigating the reverse causality issue.

[10]See Supporting Information Appendix A.6 for details.

[11]To validate this assumption we regressed the daily measure of the competitive position on separate dummies for each day in the update windows (similar to our analysis in Section 4.2.1) and find no significant differences.

We estimate short-run effects, which has both advantages and disadvantages. We want to know which contribution patterns are associated with a stronger platform. Exploring these patterns *conditional* on the competitive position lets us draw conclusions on how certain aspects of volunteer contributions distinguishes a more successful platform from a less successful one, that is, how they may form the basis of a competitive advantage in our context. However, we forego exploring long-term effects in favor of a clean identification of these short-term effects.

3.4 | Samples and variables

We decompose activity in wiki communities into the extensive margin, that is, how many members contribute, and the intensive margin, that is, how much each member contributes to a wiki. Further, highly productive contributors (HPCs) may exhibit different contribution patterns than others. We thus study contributions at two levels. At the wiki level, we identify the effect of a platform's competitive position on aggregate contributor activity as well as on the extensive margin. We then investigate the intensive margin as well as heterogeneity across contributor types at the contributor level.

3.4.1 | Wiki-level analysis

In a first step, we are interested in the *aggregate effects* of the competitive position, that is, how it relates to the total level of activity in a wiki community. Here, we use the total number of contributions made to that wiki on a given day as dependent variable.[12] Next, we evaluate the effects at the *extensive margin*, that is, how many members are contributing. Consequently, we use the number of *active contributors* who made at least one contribution to a wiki on a given day as dependent variable. As we are interested in the behavior of unpaid contributors, we disregard revisions made by platform staff and bot accounts in the construction of our dependent variables.

We use several control variables and fixed effects to account for potential confounding factors. First, we argued that community size is likely an important element of the relationship between the competitive position and contributor activity as it determines the social benefits they can derive. To tease apart the influence of relative platform strength and pure size effects we add a measure of community size at the beginning of an update window as control in some of our models. Specifically, we use the number of unique active community members over the preceding 30 days to evaluate to what extent contribution patterns are driven by social benefits or status- and impact-related motivations. We further include the interaction of community size with the *Post*-indicator to estimate our main conditional treatment effect. Second, while we exclude contributions made by platform staff from our regression samples, we do add their daily number as a control throughout the analysis.

[12]Note that this measure does not distinguish between different types of activity, that is, next to additions to a wiki's content it also contains revisions that undo prior contributions, as well as very minor ones, such as fixing a typo or adding punctuation marks. As an alternative measure for activity, we also run all analyses using a measure of content growth instead. Specifically, we use information about how many characters are added (or removed) with a certain contribution, which we aggregate to the wiki-day-level. As a result, it is a measure of how much output is actually produced. Results are comparable and presented in Supporting Information Appendix A.1.

These contributions are a direct way for the platform to engage in content creation on the wikis. Therefore, they may be linked to its competitive position in a domain. In addition, these contributions are likely to affect the behavior of unpaid contributors, either by laying the foundation for follow-on contributions or by crowding-out their activity, making it necessary to control for them.

We also add three sets of fixed effects.[13] First, we include weekday dummies. For example, if updates are released just before the weekend for some games, a weekend effect may confound our results. Second, we include dummies for each of the 23 wikis used in our analysis to account for time-invariant differences. Most prominently, some wikis enjoy the official endorsement of the game creator, which may drive differences in each platform's competitive position within that domain. By including this set of dummies we explore *within-wiki* variation only. In addition, as each wiki is specific to a platform, this set of dummies also accounts for unobserved platform characteristics. Third, we include dummies for each of the 443 game updates. This accounts for time-varying game-specific unobservables, for example, the size of its player base at the time of the release of an update. As such, it also accounts for the total number of contributors to wiki communities across both platforms covering that game. In addition, the updates may differ in the amount of changes and new features they introduce to the game, which may affect our estimation of the treatment effects. By including this set of dummies we essentially equalize the treatment intensity across updates, and we explore variation that exclusively stems from differences in contributor behavior just before and after each update. The econometric model[14] we use here is given by:

$$Y_{igt} = \beta_0 + \beta_1 \cdot \text{Post}_{gt} + \beta_2 \cdot \text{CP}_{ig\tau} + \beta_3 \cdot \text{Post}_{gt} \cdot \text{CP}_{ig\tau} + \text{Controls} + \text{Fixed Effects} + \epsilon, \tag{1}$$

with Y_{igt} being the respective outcome for platform i's wiki covering game g on day t and Post_{gt} a dummy indicating observations after the release of an update for g. The term $\text{CP}_{ig\tau}$ refers to platform i's competitive position in the coverage of game g during the update time window τ, and ϵ is the error term. We estimate the average treatment effect of game updates and are particularly interested in heterogeneity along $\text{CP}_{ig\tau}$. This can be retrieved via $\widehat{\beta}_1 + \widehat{\beta}_3 \cdot \text{CP}_{ig\tau}$.

We use the natural logarithm[15] of all our outcome and control variables to evaluate percentage changes. This lets us assess the economic significance of our effects, and evaluating (semi-)elasticities lets us compare effect sizes across different models and samples.

3.4.2 | Contributor-level analysis

To study the intensive margin, we move to a daily panel of individual contributors. We use all contributors with a minimum of 30 lifetime contributions to the respective wiki and whose activity spans a minimum of 30 days. The vast majority of contributors in our raw data make only a single contribution, and exploring their contribution patterns would offer little insight. Instead, we explore how the competitive position relates to the motivation of existing and regular contributors. Again, we exclude platform staff and bot accounts. We only use 21 wikis and

[13]Our results are robust to a wide range of alternative specifications.

[14]We assume a linear relationship in our main models, but look for potential nonlinearities in Supporting Information Appendix A.3.

[15]We add one to each variable to not lose observations with value zero.

441 patches here because two wiki communities[16] do not have any contributors that satisfy our inclusion criterion in any of the relevant update time windows. In total, our sample consists of 1,213 contributors across all wiki communities on the two platforms.

Similar to our wiki-level analysis, we use the daily number of contributions an individual makes to the wiki as dependent variable and add several control variables and fixed effects to account for unobservables. We add the same wiki-level controls as before: community size at the release of an update (as well as its interaction with the *Post*-indicator) and the number of contributions made by platform staff on a day. Moreover, as a contributor's behavior may be linked to her experience, we control for the total number of contributions she has made to the wiki up until the previous day. We again use game update and weekday fixed effects, and add contributor fixed effects. Hence, we explore within-contributor variation only, letting us interpret our results as changes in their behavior. The econometric model then is

$$Y_{kigt} = \beta_0 + \beta_1 \cdot \text{Post}_{gt} + \beta_2 \cdot \text{CP}_{ig\tau} + \beta_3 \cdot \text{Post}_{gt} \cdot \text{CP}_{ig\tau} + \text{Controls} + \text{Fixed Effects} + \epsilon, \tag{2}$$

with the only difference to (1) being that the outcome variables, denoted by Y_{kigt}, are specific to contributor k who is active in the wiki covering game g on platform i. The estimated treatment effect is also retrieved via the term. As before, we use the natural logarithm[17] of all outcome and control variables to obtain (semi-)elasticities.

Finally, we explore heterogeneity in the competition-activity link across different contributor types to ask if HPCs exhibit different contribution patterns. We identify HPCs based on the number of prior contributions they have made to a wiki up until the previous day and construct a dummy equal one if they belong to the top 10% of contributors in their wiki.[18] We add this dummy to run a three-way interaction with our *post*-dummy and our measure of competitive position.

4 | RESULTS

We first provide descriptive statistics for our key variables at the wiki and the contributor level. Second, we present and discuss our results on the aggregate effects of platform competitive position on contributor activity. Third, we separate these into changes at the extensive and intensive margin. Fourth, we further analyze the intensive margin by looking at different contributor types. Finally, we run additional analyses to further test the underlying mechanisms. We run OLS regressions throughout[19] and cluster standard errors at the level of the panel unit.[20]

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[16]"For Honor" and "Rocket League" on Gamepedia.

[17]We add one to each variable to not lose observations with value zero.

[18]Using the top 5% or 25% does not change the conclusions drawn from our analysis. However, the effect gets stronger yet more noisy the more restrictively we define HPCs.

[19]In cases where our outcome of interest is a count variable (e.g., daily contributions), Poisson regressions give the same results.

[20]Alternatively, we could cluster standard errors at the game level as our treatment (the updates) are administered at this level. Our results are qualitatively the same, but the precision of the estimates is lower, in particular for very low and very high competitive position levels. However, the low number of clusters (representing the 13 games in our sample) can be problematic and lead to inflated standard errors (Cameron & Miller, 2015). We therefore still use panel-unit clustering as our preferred specification.

TABLE 1 Descriptive statistics: Wiki level

		Absolutes				Logarithms			
	Observations	Mean	*SD*	Min	Max	Mean	*SD*	Min	Max
Contributions	6,999	24.66	48.85	0	428	1.95	1.68	0	6.06
Active contributors	6,999	5.30	10.27	0	113	1.17	1.06	0	4.74
Post	6,999	0.56	0.50	0	1				
Competitive position	6,999	0.56	0.28	0.014	1				
Community size	6,999	88.60	153.72	0	1,354	3.43	1.53	0	7.21
Staff contributions	6,999	1.85	13.22	0	244	0.18	0.71	0	5.50

4.1 | Descriptive statistics

4.1.1 | Wiki level

Table 1 contains summary statistics for our wiki-level variables.[21] We present absolute values to give some intuition about our setting and data. The 443 nine-day update windows and 23 wikis we use result in a total of 6,999 observations. On average and per day, wiki communities have 5.3 active contributors and 24.66 contributions. Note that our sample contains values considerably higher than that, for example, the maximum value for the daily contributions is 428, even after excluding outliers.[22] We also ran all our estimations including these outliers as well as excluding more, with identical results. As we count the release date of an update as part of the treated group in our research design, 56% of all observations in our sample are treated. Also, the variable measuring a platform's competitive position in a domain is 0.56 on average. While for games covered on both platforms this measure adds up to one for the two wikis (i.e., an average of 0.5 per domain), this is not the case for the three exclusive games, taking the average above 0.5. The distribution of values is shown in Figure 2a, with some bunching at the upper end (CP = 1), suggesting that observations associated with exclusive wikis are more frequent than other values. On average, a wiki features a community size of 88.60 unique active users over the preceding 30 days at the beginning of a time window (also subject to a skewed distribution), and platform staff contributes 1.85 times per day.

4.1.2 | Contributor level

Contributor-level summary statistics are in Table 2.[23] Here, we can only use 441 updates and 21 wikis, giving a total of 1,213 contributors and a total sample size of 234,361 observations. On average, a community member makes 0.39 daily contributions to a wiki. Values in the data follow a long tail distribution, with the maximum being 508. Again, excluding outliers from the analysis does not affect our results. As before, 56% of all observations are treated in our sample.

[21]Table A9 contains the correlation matrix for our wiki-level variables.

[22]For observations just before and just after the release of an update we excluded observations that exceed the respective 99th percentile of the number of contributions to a wiki on a day.

[23]Table A10 contains the correlation matrix for our contributor-level variables.

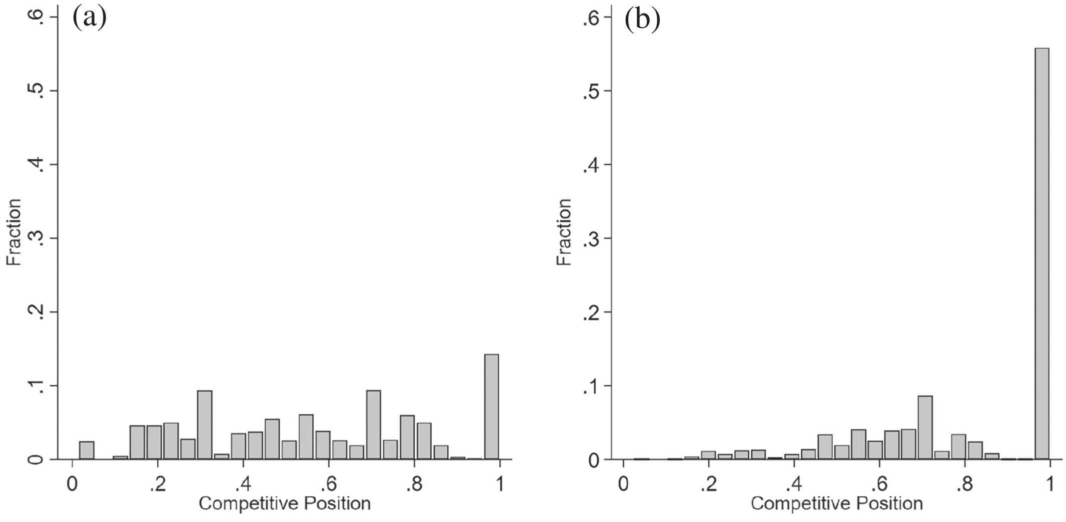

FIGURE 2 Distribution of competitive position levels. (a) Wiki level and (b) contributor level

TABLE 2 Descriptive statistics: Contributor level

		Absolutes				Logarithms			
	Observations	Mean	*SD*	Min	Max	Mean	*SD*	Min	Max
Contributions	234,361	0.39	4.69	0	508	0.08	0.40	0	6.23
Post	234,361	0.56	0.50	0	1				
Competitive position	234,361	0.82	0.23	0.02	1				
High-productivity contributor	234,361	0.11	0.31	0	1				
Community size	234,361	263.37	237.02	0	1,354	4.95	1.32	0	7.21
Staff contributions	234,361	1.20	9.00	0	254	0.19	0.64	0	5.54
Prior contributions	234,361	279.67	1,131.66	0	31,004	4.37	1.39	0	10.34

Here, the mean of the variable measuring the competitive position is 0.82, so that stronger-positioned wikis are overrepresented. Figure 2b confirms this intuition, with pronounced bunching at the top end of the distribution. Exclusive wikis alone account for around 60% of all observations due to our inclusion criterion for contributors (30 + lifetime contributions and continued engagement over 30 + days). In domains where platforms are lagging behind there are hardly any HPCs. Of these, 11% of observations are made by contributors defined as highly productive. Further, each day, the average community member has made 279.67 prior contributions, again following a pronounced long-tail distribution. Regarding our wiki-level constructs, average community size at the beginning of an update window is 263.37 (slightly higher than in the wiki-level sample and driven by the skewed distribution of competitive position so that larger wikis are represented more strongly in this sample), while the value for staff contributions is slightly lower at 1.20.

TABLE 3 Updates as an impulse to contributor activity

	Contributions	
	(1) Wiki level	(2) Contributor level
Post	0.2653 [0.0002]	0.0282 [0.0000]
Community size	0.4671 [0.0000]	0.0170 [0.3290]
Prior contribution		−0.0092 [0.1760]
Staff contribution	0.0219 [0.4502]	0.0077 [0.0146]
Constant	0.1950 [0.2496]	0.0160 [0.8645]
Observations	6,999	234,361
Adjusted R^2	0.7027	0.2619
Within-R^2	0.0454	0.00209

Note: *p* values in brackets. Standard errors clustered at the level of the panel unit. Models include update, wiki (Model 1) or contributor (Model 2), and weekday fixed effects.

4.2 | Regression analysis

4.2.1 | Updates as an impulse to contributor activity

An important requirement for our identification strategy to work is that updates act as an impulse to contributor activity.[24] To evaluate this, we first estimate their treatment effects without exploring heterogeneous effects.

Wiki-level results are presented in Model 1 of Table 3. Using the number of contributions as the dependent variable, the estimated coefficient for the post-dummy is positive and statistically significant ($\widehat{\beta}=0.2653$, $p = .0002$), so that activity in a wiki is indeed higher just after the release of an update compared to just before. Specifically, the number of contributions is 30.38% higher for treated observations[25] on average. We estimate the same model using separate dummies for each day of the update window instead in Model 2 and plot the estimated coefficients in Figures 3a.[26] The pattern we observe is in line with expectations: Using $t = -4$ as our baseline, activity levels just before an update are not statistically distinguishable from one another, but we observe a sharp increase on the day of an update's release. This increase fades away over the next days, reverting to its original levels. These results indicate that updates indeed trigger contributor activity at the wiki-level.

We run similar regressions at the contributor level. As we include contributor fixed effects throughout, this analysis evaluates to what extent updates induce each contributor to increase their efforts. Results are in Model 3 of Table 3, and we find that daily contributions are 2.82% higher just after an update compared to just before ($\widehat{\beta}=0.0282$, $p = .0000$), on average. Again, we use separate dummies for each day (Model 4 of Table 3), and plot the coefficients in Figure 3b. The pattern is very similar to the wiki-level analysis, and in line with expectations. At the same time, the effects at the contributor level are considerably smaller than at the wiki level.

[24]To test the validity of our identification strategy, we ran a pretrend analysis, which is provided in Supporting Information Appendix A.4.

[25]Effect sizes are obtained via $\exp\left(\widehat{\beta}_2\right)-1$, with $\widehat{\beta}_2$ being the estimated coefficient for the post-dummy.

[26]Regression results are reported in Table A11.

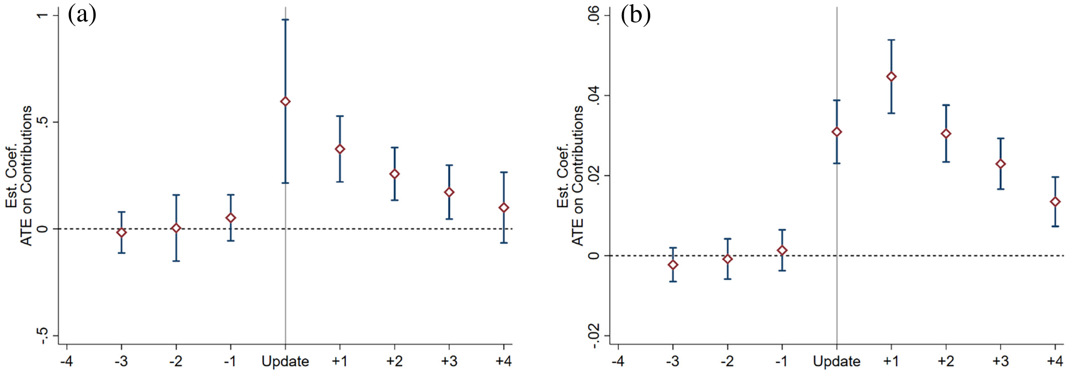

FIGURE 3 Updates as an impulse to contributor activity. (a) Wiki level and (b) contributor level

4.2.2 | Aggregate effects and the platform's competitive position

We now turn to the role of a platform's competitive position at the wiki level. Recall that we are interested in the interaction between the competitive position at the beginning of an update time window and the post-dummy, thus exploring heterogeneity in the treatment effect of updates. We investigate total activity at the wiki level, that is, we do not yet look at disaggregated effects at the intensive and extensive margins.

Model 1 of Table 4 reports the results using the number of daily contributions as outcome variable. Here we do not (yet) control for community size effects. The estimated coefficient for the post-dummy is statistically indistinguishable from zero. However, its interaction with a platform's competitive position is positive and precisely estimated ($\widehat{\beta}=0.5090$, $p = 0.0008$). The coefficients for the average treatment effect at different levels of CP are in Figure 4a. The effect of updates is stronger the stronger a platform's competitive position. Specifically, at the low end of the spectrum there is no increase in activity following an update. Thus, in domains where a platform is weak compared to its rival, contributors do not exert effort to compile information about the changes brought about by an update. However, at the other end of the spectrum, that is, in domains where a platform is the single host of all contributors (CP = 1), we find that effects are strongest with 62.14% more contributions made just after the release of an update compared to just before.[27] Finally, in domains where the two platforms are even (CP = 0.5), we obtain positive, but weaker effects, with daily contributions being 25.71% higher.

To tease apart the influence of the competitive position and pure community size effects we add community size and its interaction with the post-dummy in Model 2 of Table 4. The interaction tells us to what extent the treatment effect of updates is driven by variation in community size. We estimate a positive and marginally significant coefficient ($\widehat{\beta}=0.0541$, $p = .0654$), suggesting that activity increases are driven by a larger community. More importantly, we still obtain a positive coefficient on the interaction of the competitive position and the post-dummy, which however is slightly smaller compared to Model 1 and estimated less precisely ($\widehat{\beta}=0.3289$, $p = .0434$). We again plot the treatment effects at different levels of the competitive position in Figure 5a, which shows very similar, yet slightly less pronounced patterns.

[27]Effect sizes for different levels of the competitive position are calculated as $\exp\left(\widehat{\beta}_2 + \mathrm{CP} \times \widehat{\beta}_3\right) - 1$, with $\widehat{\beta}_2$ being the estimated coefficient for the post-dummy, and $\widehat{\beta}_3$ for the interaction term with CP.

TABLE 4 Wiki level results

	Contributors		Active contributors	
	(1)	(2)	(3)	(4)
Post	−0.0257 [0.6822]	−0.1098 [0.1599]	−0.0270 [0.5404]	−0.1114 [0.0296]
Post × competitive position	0.5090 [0.0008]	0.3289 [0.0434]	0.2598 [0.0149]	0.0805 [0.1783]
Post × community size		0.0541 [0.0654]		0.0540 [0.0012]
Competitive position	0.1562 [0.6512]	0.0770 [0.7212]	−0.1567 [0.4518]	−0.1666 [0.1062]
Community size		0.4320 [0.0000]		0.2543 [0.0000]
Staff contribution	0.0137 [0.5978]	0.0145 [0.5797]	0.0172 [0.2758]	0.0175 [0.2596]
Constant	1.7135 [0.0000]	0.2771 [0.0609]	1.1911 [0.0000]	0.3250 [0.0041]
Observations	6,999	6,999	6,999	6,999
Adjusted R^2	0.6966	0.7050	0.8198	0.8285
Within-R^2	0.0257	0.0531	0.0236	0.0707

Note: *p* values in brackets. Standard errors clustered at the level of the wiki. All models include update, wiki, and weekday fixed effects.

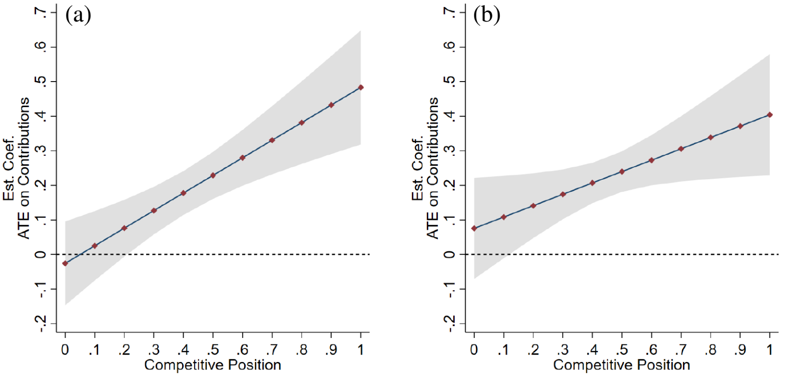

FIGURE 4 Wiki-level effects: Contributions. (a) Without community size control and (b) with community size control

Together, these findings reveal several aspects about how the competitive position relates to contributor activity. First, they show that a stronger positioned platform indeed has an advantage in terms of value creation. Second, this advantage is only partly driven by community size effects, and there is considerable residual variation associated with the competitive position.

4.2.3 | Effects at the extensive margin

In our analysis on the extensive margin of contribution activity, we use the number of daily active contributors as dependent variable and present results in Models 3 and 4 of Table 4. First, we again run a model without controlling for community size effects (Model 3). The estimated coefficient on the interaction between competitive position and post-dummy is positive and

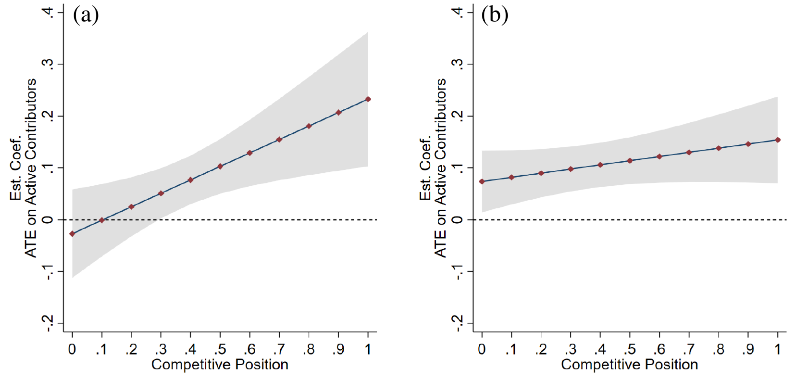

FIGURE 5 Wiki-level effects: Active contributors. (a) Without community size control and (b) with community size control

significant ($\widehat{\beta}$=0.2598, p = .0149). We also plot the update treatment effects at different levels of the competitive position in Figure 5a, revealing a similar pattern as in our analysis of the aggregate effects: At the lower end of the spectrum, there is no increase in daily active users just after the release of an update. Again, the greatest treatment effect can be found at the high end of the spectrum, suggesting that 26.21% more contributors are active just after an update compared to just before. In the case of neck-on-neck competition (CP = 0.5) 10.83% more contributors are active. A stronger platform's advantage seems partly driven by the extensive margin of value creation; more contributors come together to engage in collaborative output production. However, comparing effect sizes here with those for aggregate effects suggests that the extensive margin does not tell the whole story.

We add the community size control and its interaction with the post-dummy in Model 4 of Table 4. The estimated coefficient is positive and significant ($\widehat{\beta}$=0.0540, p = .0012): In domains where a platform exhibits a larger community size (as measured by unique users over the preceding 30 days at the beginning of an update time window), more contributors come together to compile the changes associated with an update. This simply tells us that a larger community can deploy more active members at any given time. More importantly, the coefficient on the interaction between competitive position and post-dummy is insignificant in this specification. This is illustrated by the plot of treatment effects for different levels of competitive position in Figure 5b, which is rather flat.

These findings suggest that the extensive margin is an important element of a stronger platform's advantage. Model 3 of Table 4 shows that in areas where its contributors have produced relatively more output than its rival, a larger number of them engages in collaborative value creation at any point in time. The results of Model 4 show that this is driven by the fact that stronger platforms have larger communities. Put simply, a stronger platform benefits from greater "manpower", driving part of its competitive advantage in terms of value creation.

4.2.4 | Effects at the intensive margin

We now take a closer look at the intensive margin of value creation, that is, how much each individual community member contributes. We move the analysis to the contributor-level with fixed effects to evaluate changes in individual behavior. We use daily contributions at the individual level as dependent variable and present results in Table 5.

Similar to our wiki-level analyses we do not include community size as control in Model 1. The estimated coefficient for the post-dummy is statistically indistinguishable from zero. Its interaction with competitive position (our coefficient of interest) is positive, but only marginally significant ($\widehat{\beta}$=0.0209, p = .0596). This provides some evidence that each contributor increases their activities just after an update. We plot the coefficients at different levels of CP in Figure 6a. Similar to previous findings, the effects are not statistically significant for low values of CP. However, the estimates in this region are very imprecise, which may be due to the low number of observations (recall the distribution of observations in Figure 2b). We again find the strongest effects at the opposite end of the spectrum (CP = 1) with community members increasing their contributions by 3.24% just after the release of an update. In domains where platforms are level, we observe 2.22% more contributions. Hence, activity increases induced by an update do depend positively on the competitive position. However, effect sizes are considerably smaller than both the aggregate effects and the effects at the extensive margins. In addition, the association between competitive position and activity increases is far less pronounced.

In Model 2, we add community size controls. Here, we estimate a positive and highly significant coefficient on its interaction with the post-dummy ($\widehat{\beta}$=0.0105, p = .0000), showing that each contributor's activity increase after an update is stronger in larger communities. This highlights the importance of social benefits in driving participation. Consistent with earlier findings (Zhang & Zhu, 2011), having peers to collaborate with is an important motivational source. In addition, the coefficient on the interaction between the competitive position and the post-dummy is insignificant in this model. Thus, the association between competitive position and update treatment effects becomes flat (Figure 6b). Hence, the (slight) positive association found in Model 1 of Table 5 appears completely driven by community size.

These results provide some evidence that a stronger competitive position is associated with increased activity at the intensive margin of value creation, but through the channel of larger community size. Each community member contributes slightly more in domains where a platform is stronger. However, comparing effect sizes here with those obtained earlier suggests that the extensive margin is a relatively more important element of the competitive advantage than the intensive margin of value creation.

4.2.5 | High-productivity contributors

We now turn to contributor heterogeneity. Specifically, HPC, that is, the top 10% in terms of prior contributions, may display different activity patterns as they may enjoy nonpecuniary benefits that are not tied to a higher number of potential collaborators. We allow the heterogeneity in treatment effects of updates along the competitive position to vary by contributor type by including a three-way interaction of the post-dummy, platform competitive position in a domain, and a dummy for HPC.[28]

We present the results in Models 3 and 4 of Table 5. In Model 3, we do not control for community size effects and estimate a positive and statistically significant coefficient for our three-way interaction ($\widehat{\beta}$=0.1178, p = .0329). All other estimated coefficients involving the post-dummy are statistically indistinguishable from zero. This suggests a positive relationship between the strength of the update treatment effect and the competitive position for HPCs, but not others.

[28]As the identification of HPC is based on prior contributions, we do not include this measure as control in the same regressions.

TABLE 5 Contributor-level results

	Contributions			
	(1)	(2)	(3)	(4)
Post	0.0110 [0.2476]	−0.0125 [0.2371]	0.0071 [0.3578]	−0.0184 [0.0407]
Post × CP	0.0209 [0.0596]	−0.0133 [0.2536]	0.0129 [0.1364]	−0.0229 [0.0198]
Post × HPC			0.0060 [0.8923]	0.0096 [0.8279]
Post × CP × HPC			0.1178 [0.0329]	0.1143 [0.0374]
Post × community size		0.0105 [0.0000]		0.0111 [0.0000]
Competitive position (CP)	−0.1313 [0.3784]	−0.1268 [0.4041]	−0.1502 [0.3610]	−0.1427 [0.3903]
HPC			−0.0579 [0.4708]	−0.0580 [0.4741]
CP × HPC			−0.0729 [0.4758]	−0.0730 [0.4779]
Community size		0.0136 [0.4359]		0.0118 [0.4968]
Staff contribution	0.0079 [0.0098]	0.0073 [0.0160]	0.0081 [0.0085]	0.0075 [0.0145]
Prior contribution	−0.0091 [0.1790]	−0.0090 [0.1830]		
Constant	0.2075 [0.0982]	0.1363 [0.3569]	0.1974 [0.1448]	0.1326 [0.4031]
Observations	234,361	234,361	234,596	234,596
Adjusted R^2	0.2620	0.2622	0.2611	0.2614
Within-R^2	0.00214	0.00247	0.00476	0.00510

Note: p values in brackets. Standard errors clustered at the level of the contributor. All models include update, contributor, and weekday fixed effects.

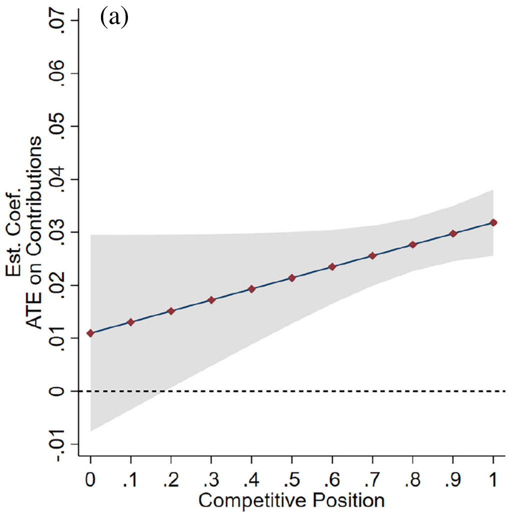

FIGURE 6 Contributor-level effects. (a) Without community size control and (b) with community size control

In Model 4, we add our community size control. Again, we estimate a positive and statistically significant coefficient on its interaction with the post-dummy, confirming the importance of positive side effects. However, the coefficient on our three-way interaction remains positive, statistically significant, and of similar magnitude as before ($\widehat{\beta}=0.1143$, $p = .0374$). Hence, the treatment effect of updates is stronger for HPCs and increasing in a platform's (relative) competitive position.[29] Based on this specification, we plot the estimated coefficient of the post-dummy for different levels of CP, and for the different contributor types in Figure 7, illustrating three important findings: First, there is a strongly positive relationship between a platform's competitive position and the strength of the treatment effect of updates for HPC, but not for others. In fact, we estimate a slight negative association for non-HPCs, which may suggest that they are crowded out by HPCs on a stronger platform. This positive relationship for HPCs persists after controlling for community size, suggesting that they are not only driven by the presence of potential collaborators. This pattern is consistent with status- or impact-related sources of motivation accruing from the fact that HPCs develop a sense of ownership and ego-gratification from being the main drivers of relative platform success. Third, the fact that their activity increases only occur on a stronger platform suggests that the activity of this relatively small group of core community members is an important driver of a leading platform's competitive advantage in value creation.

4.3 | Further analyses

4.3.1 | Relative importance of the extensive and intensive margins

We found sizable differences in the estimated treatment effects by a platform's competitive position. These differences are driven by changes both at the extensive and intensive margins of

[29]In Supporting Information Appendix A.3, we show that this is largely driven by exclusive wikis, which we attribute to status- and impact-related benefits being highest there.

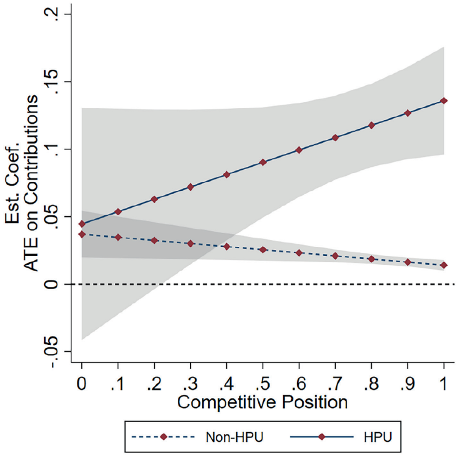

FIGURE 7 Contributor-level effects: Heterogeneity across contributor types

content creation. To assess if changes in overall contributions are mainly driven by a higher number of active contributors or by each active contributor increasing their efforts, we run a series of simulations: We define four levels of the competitive position for ease of exposition: *Laggard* (CP ≤ 0.33), *Neck-on-Neck* ($0.33 <$ CP ≤ 0.67), *Leader* ($0.67 <$ CP <1), and *Exclusive* (CP $= 1$). For each, we separately calculate the percentage change in total contributions triggered by the release of an update. We obtain its level in the *Pre*-period by simply multiplying the average number of active users in a wiki and per day (i.e., the extensive margin), denoted by $\overline{n}_{\text{Pre}}$, with the average level of contributions by each active contributor (i.e., the intensive margin), $\overline{y}_{\text{Pre}}$. Further, for the intensive margin, we obtain averages for HPCs and others separately, and we weigh each by its share of total contributions. The calculated outcome is then given by:

$$Y_{\text{Pre}} = \overline{n}_{\text{Pre}} \cdot \left(s_{\text{Pre}}^{\text{HPC}} \cdot \overline{y}_{\text{Pre}}^{\text{HPC}} + \left(1 - s_{\text{Pre}}^{\text{HPC}}\right) \cdot \overline{y}_{\text{Pre}}^{\text{Non-HPC}}\right), \tag{3}$$

where ${s_{\text{Pre}}}^{\text{HPC}}$ denotes the share of contributions attributable to HPCs.

Next, to predict the contribution levels in the *Post*-period we use our estimates for the conditional average treatment effects (CATE) for the relevant outcomes.[30] The idea is to obtain the percentage change in an outcome of interest between the *Pre*- and *Post*-periods. Based on this and for each level of a platform's competitive position, we calculate the predicted number of active users in the *Post*-period as $\widehat{n}_{\text{Post}} = \overline{n}_{\text{Pre}} \cdot \left(1 + \widehat{\Delta n}\right)$, with $\widehat{\Delta n}$ denoting the estimated CATE.[31] Analogously, we calculate the predicted change at the intensive margin (again separately for HPCs and non-HPCs) as $\widehat{Y}_{\text{Post}} = \overline{y}_{\text{Pre}} \cdot \left(1 + \widehat{\Delta y}\right)$. Together, this lets us predict the total number of contributions in the *Post*-period as

[30]Recall that the CATE can be calculated as $\exp\left(\widehat{\beta}_2 + \text{CP} \times \widehat{\beta}_3\right) - 1$, with $\widehat{\beta}_2$ being the estimated coefficient for the post-dummy, and $\widehat{\beta}_3$ for the interaction term with CP.

[31]For example, the average number of active contributors in the *Pre*-period and for the *Neck-on-Neck* position is 3.87. From our regression Model 3 of Table 4, we retrieve the estimated CATE as 0.11. The predicted number of active contributors in the *Post*-period is then calculated as $3.87 \times 1.11 = 4.29$.

$$\widehat{Y}_{\text{Post}} = \widehat{n}_{\text{Post}} \cdot \left(s_{\text{Post}}^{\text{HPC}} \cdot \widehat{Y}_{\text{Post}}^{\text{HPC}} + \left(1 - s_{\text{Post}}^{\text{HPC}}\right) \cdot \widehat{Y}_{\text{Post}}^{\text{Non-HPC}} \right). \tag{4}$$

Finally, with (3), we compute the percentage change in contributions between the *Pre*- and *Post*-periods as

$$\widehat{\Delta Y} = \frac{\widehat{Y}_{\text{Post}} - Y_{\text{Pre}}}{Y_{\text{Pre}}}. \tag{5}$$

In this approach, all parameters used are either true sample means or easily computed based on estimated coefficients.[32] Moreover, this simple setup lets us simulate different scenarios easily.

To tease out the relative importance of extensive and intensive margins in content creation, we simulate five scenarios: First, and as a baseline ("Full" scenario), we calculate the full prediction according to (5). Second, we simulate a situation in which there are no changes at the intensive margin between the *Pre*- and *Post*-periods by setting parameters $\widehat{\Delta y}_{\text{HPC}}$ and $\widehat{\Delta y}_{\text{Non-HPC}}$ to zero to predict the change in total contributions to a wiki if only the number of active contributors changes. We call this scenario "Extensive Margin". Third, we simulate a situation in which changes only occur at the intensive margin by setting parameter $\widehat{\Delta n}$ to zero, predicting total contributions if the number of active contributors stays the same, but each adjusts their efforts. We call this scenario "Intensive Margin". Lastly, we run two additional simulations to distinguish between changes at the intensive margin for HPCs and non-HPCs. Again, in both we set parameter $\widehat{\Delta n}$ to zero, and in scenario "Intensive Margin (non-HPC)" parameter $\widehat{\Delta y}_{\text{HPC}}$ is set to zero, while in scenario "Intensive Margin (HPC)" parameter $\widehat{\Delta y}_{\text{Non-HPC}}$ is set to zero. In both, we predict the total contributions if the number of active contributors stays the same, and only one type of contributor adjusts their effort.

We plot the predicted changes in the number of contributions for each scenario and at different levels of the competitive position in Figure 8.[33] Under the "Full" scenario, the change from *Pre* to *Post* is larger the stronger the competitive position. We see similar patterns for the scenarios "Extensive Margin", "Intensive Margin", and "Intensive Margin (HPC)". For "Intensive Margin (non-HPC)", this is not the case—in fact, we see decreases in activity that get stronger the stronger the competitive position is. Next, while the general relationship between competitive position and predicted changes is similar across these scenarios, we document differences in the relative importance of the extensive and intensive margins. Most notably, the percentage increases attributable to the extensive margin are considerably higher than those at the intensive margin (for HPCs). In addition, the increases in activity along the competitive position is much more pronounced for the extensive margin. Hence, when it comes to activity measured as daily contributions, a stronger platform is at an advantage mainly because of the higher number of contributors. In addition, the intensive margin also explains a meaningful increase in wiki-level contributions. However, this channel is driven by a small subset of HPCs, and its influence is not as strong as the extensive margin.

[32]We provide an overview of all used parameters in Table A12.

[33]Note that, despite the additive setup, the changes under "Intensive Margin" and "Extensive Margin" need not add up to the changes under "Full" due to the weighting by the share of HPCs (s^{HPC}) which differs between the *Pre* and *Post* periods.

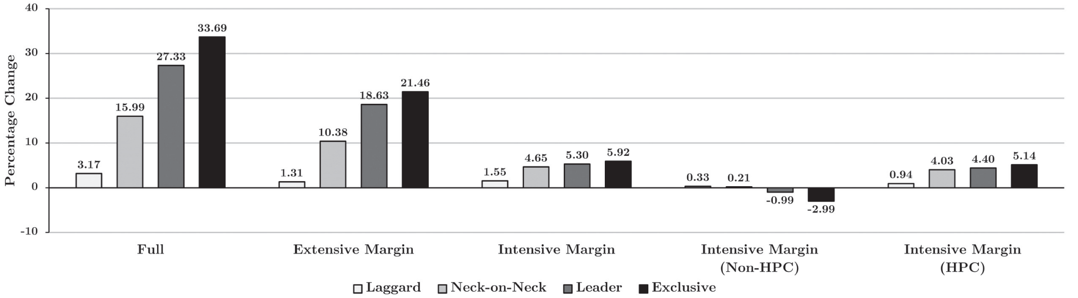

FIGURE 8 Simulation: Predicted changes in contributions

4.3.2 | Reverts and maintenance

Recall that the relationship between a platform's competitive position and contributors' nonpecuniary benefits are at the core of our argument. At the same time, a stronger competitive position may also entail the need for increased engagement in coordination and quality control if it is associated with a larger number of contributors. Hence, part of what we observe may not reflect content creation, but rather its maintenance.

We test this at the contributor level using two different outcome variables: First, one way to ensure high-quality content on a wiki is to simply undo contributions by others, for instance if they contain false information or constitute vandalism. As this is a built-in feature of both platforms, *reverts* are automatically flagged in the comments attached to each contribution. Using this information, we identify 3.5% of all contributions as reverts. Second, aside from flat-out undoing contributions by others, community members can engage in more subtle quality-control, for example, by correcting spelling or grammar errors contained in articles, or by changing its format. Here, neither new content is created, nor is existing content altered extensively. To identify such *maintenance* contributions, we use insights from the pages detailing the exact differences between two stages of an article.[34] Here, we evaluate whether or not its informational content is altered, which we consider to be the case if at least one of the two following conditions is met: First, relevant information in video games often comes in digits, for example, how much damage a certain weapon inflicts, or how much health points certain enemies possess. Therefore, we consider it a change in an articles' informational content if at least a single digit is altered with a contribution. Second, we identify a change if the article text is changed significantly. Here, we evaluate the overlap in the character strings[35] in the altered sections of the articles before and after the contribution, and consider values below 90% to constitute a meaningful change in content. We flag a contribution as maintenance if *neither* of the two conditions is met, that is, the informational content is *not* altered. This identifies 29.34% of contributions as maintenance.

Finally, to investigate if HPC's efforts are exclusively focused on these policing and maintenance activities, we run a third set of regressions using a measure of "content growth". It is based on information about how many characters are added or removed with a contribution. Here, we aggregate this to the daily contributor level. Hence, it measures the amount of content

[34]Recall that both platforms provide a detailed overview of the parts of an article that are altered with each contribution. Figure A5 provides an example of such a page.
[35]We again use the Python package "FuzzyWuzzy" to calculate this similarity score.

TABLE 6 Additional analysis: Reverts and maintenance

	Reverts		Maintenance		Content growth	
	(1)	(2)	(3)	(4)	(5)	(6)
Post	−0.0025 [0.0821]	−0.0010 [0.3813]	−0.0050 [0.2601]	−0.0050 [0.1320]	−0.0414 [0.2024]	−0.0453 [0.1082]
Post × CP	0.0020 [0.3226]	−0.0001 [0.9611]	0.0001 [0.9849]	−0.0058 [0.1687]	−0.0398 [0.2525]	−0.0796 [0.0100]
Post × HPC		−0.0108 [0.1080]		−0.0101 [0.6714]		−0.0691 [0.6063]
Post × CP × HPC		0.0168 [0.0685]		0.0580 [0.0516]		0.4261 [0.0097]
Post × community size	0.0003 [0.4007]	0.0002 [0.4448]	0.0028 [0.0002]	0.0030 [0.0001]	0.0316 [0.0000]	0.0336 [0.0000]
Competitive position (CP)	−0.0154 [0.5821]	−0.0191 [0.5444]	0.0158 [0.7513]	0.0077 [0.8883]	−0.4237 [0.3118]	−0.4950 [0.3080]
HPC		−0.0153 [0.3660]		−0.0210 [0.5316]		−0.1979 [0.3871]
CP × HPC		0.0305 [0.2517]		−0.0133 [0.7636]		−0.2182 [0.4431]
Community size	0.0072 [0.0539]	0.0067 [0.0710]	0.0035 [0.5414]	0.0031 [0.6017]	0.0316 [0.4611]	0.0236 [0.5850]
Staff contribution	−0.0002 [0.8004]	−0.0002 [0.8093]	0.0024 [0.1222]	0.0026 [0.0882]	0.0227 [0.0075]	0.0236 [0.0055]
Prior contribution	0.0029 [0.0435]		−0.0019 [0.5063]		−0.0270 [0.1454]	
Constant	−0.0268 [0.3745]	−0.0097 [0.7474]	−0.0023 [0.9673]	0.0022 [0.9697]	0.4745 [0.2451]	0.4976 [0.2695]
Observations	234,361	234,596	234,361	234,596	231,841	232,035
Adjusted R^2	0.2955	0.2954	0.1901	0.1887	0.2178	0.2181
Within-R^2	0.000522	0.000713	0.000856	0.00220	0.00232	0.00481

Note: *p* values in brackets. Standard errors clustered at the level of the contributor. All 6models include update, contributor, and weekday fixed effects.

she added in a day, presenting an alternative productivity measure. As before, we use its natural logarithm. Results are presented in Models 5 and 6 of Table 6 and they confirm the pattern we found in our main analysis. The estimated coefficient on the three-way interaction in Model 6 is positive and statistically significant ($\widehat{\beta}=0.4261$, $p = .0097$), hence the increase in added content caused by an update is greatest for HPCs in domains where the platform is in a better competitive position. In addition, this shows that these contributors are not only pre-occupied with policing and maintenance, but also account for the majority of newly created content.[36]

5 | DISCUSSION AND CONCLUSION

We analyze activity on two competing digital platforms organized around communities of volunteer contributors to explore if and how online communities can form the basis of a competitive advantage. We investigate how the activity of a platform's community of volunteers differs by a platform's competitive position, and which mechanisms tie macro-level platform competition to outcomes at the micro-level of contributors. We argue that the competitive position affects the number of active contributors on a platform at any time (*contributor coordination*) and each contributor's activity (*contributor motivation*), the extensive and intensive margins of value creation, respectively.

In our study of video game wikis, we find that in the context of crowd-sourced value creation, success begets success: stronger platforms have more productive volunteer communities. This advantage unfolds through three channels. First, they typically have a larger number of active contributors, providing more manpower; an advantage at the *extensive margin* of value creation. This resonates with work on how platform dominance can help resolve coordination issues (Argenziano & Gilboa, 2012; Biglaiser & Crémer, 2016; Eisenmann, Parker, & Van Alstyne, 2006). Second, a larger community provides individual members with greater social benefits (Zhang & Zhu, 2011), driving increased participation at the *intensive margin*. Finally, the most valuable group of volunteers contributes more on platforms with a stronger relative competitive position. The importance of HPCs in value creation is in line with previous findings (Gorbatai, 2014; Rullani & Haefliger, 2013; Shah, 2006), but we highlight that they are even more willing to contribute if "their" platform's competitive position is strong. Thus, competitive advantage in community-based platforms goes beyond pure size advantages and especially the most valuable contributors are motivated by factors related to the *relative* competitive position in addition to those related to *absolute* community size.

5.1 | Managerial implications

Our findings have several implications for the strategic management of crowdsourced platforms, an especially challenging context because the individuals contributing most to platform value are neither employed by the platform nor motivated by financial incentives. First, the two most important drivers of competitive advantage in value creation are greater manpower connected with a larger community size and the activity of a relatively small subset of core contributors, both of which cannot easily be replicated. Multihoming and

[36]In Supporting Information Appendix A.1, we provide additional details on this line of inquiry and we conduct an additional robustness check using another outcome variable.

switching platforms are rare in our setting, making it difficult for a weaker platform to catch up in these dimensions. Especially HPCs, who exerted considerable effort on a particular platform in the past and make significant contributions to maintain and police the platform, are unlikely to switch allegiances easily. This creates barriers to organic growth or even entry, especially for young and relatively small competitors, which makes the option of growing, or entering, through acquisition more attractive. As a case in point, Fandom acquired Gamepedia in early 2019 following years of coexistence and competition in the area of video game wikis, while in a different market, Microsoft acquired GitHub, the most popular platform for open-source software development (Sawers, 2018).

Second, our findings suggest that the extensive margin of value creation contributes more to platform advantage than the intensive margin, even when considering HPCs. Hence, strategies that grow the community seem more promising than those purely aimed at motivating existing contributors, ceteris paribus. The effect of greater manpower outweighs increased effort provision by each contributor and there may be follow-on effects on contributor effort. This is in line with the two platforms' focus on search engine optimization that emerged from interviews with them. Being ranked higher on search engines brings in more traffic, which in turn may motivate some viewers to start contributing content (Kane & Ransbotham, 2016; Nagaraj & Piezunka, 2020).

Third, HPCs play an important role both by creating content as well as policing and maintaining others'. However, while they are highly valuable for the value creation process, managing this relatively small subset of contributors is challenging. Heavy-handed attempts to control or govern their behavior may put them off and make them abandon the platform (Kretschmer et al., 2022). Interviews with platform staff confirm that especially contributors on larger wikis with established hierarchies respond adversely to governance attempts. This suggests a trade-off: On the one hand, core members emerge in successful communities and form the basis of platform competitive advantage. On the other hand, this limits the platform's control over their activities and may complicate incentive alignment.

5.2 | Contributions

We contribute to two literature streams. First, we provide novel insights about the strategic management of crowdsourced platforms by demonstrating how activity patterns shape competitive advantage in such markets. While previous studies investigated motivational sources and underlying drivers of volunteer contributions to online communities more generally (Jeppesen & Frederiksen, 2006; Lakhani & Wolf, 2005; Shah, 2006; Shah & Nagle, 2020), we explicitly lay out how they relate to a platform's relative market position. Doing so, we heed calls for more research in this area (Lerner & Tirole, 2002; von Krogh et al., 2012) by identifying some mechanisms linking the external and macro-level factors of platform competition to micro-level contributor behavior. Previous work has largely been theoretical (Athey & Ellison, 2014; Casadesus-Masanell & Ghemawat, 2006; Llanes & de Elejalde, 2013; Sacks, 2015), with the exception of Nagaraj and Piezunka (2020), who find that facing a dominant competitor deprives a platform of new contributors, but leads to an increase in the activity of already existing ones. While the underlying drivers are similar to those we propose, there are some key differences. Nagaraj and Piezunka (2020) (as well as previous theoretical studies) study competition with a dominant, *commercial* alternative. In contrast, we provide empirical evidence about competition between two crowdsourced platforms who draw from the same pool of potential (voluntary) contributors. This difference may explain a key divergence in our findings: In their study, established members increase their efforts when facing strong competition, that is, being in a *weaker* competitive position. Conversely, we find that HPCs are more active if "their" platform is in a *stronger* competitive position. Future work outlining the boundary conditions of these respective findings would be promising.

Second, we also contribute to the literature on platform competition (Cennamo & Santalo, 2013; Eisenmann et al., 2006; Halaburda & Yehezkel, 2016). Much of the existing literature studies aspects of increasing returns to scale in adoption under network effects (Katz & Shapiro, 1985; Schilling, 2003) and its limits (Zhu & Iansiti, 2012), with studies on the inner workings of platform ecosystems only recently emerging (Kretschmer et al., 2022; McIntyre & Srinivasan, 2017). We add to both conversations by investigating how between-platform competition may relate to within-ecosystem value creation processes. Similar to Boudreau and Jeppesen (2015), we study a case where complementors have no pecuniary motives. However, in their context, a platform's contributors compete with one another so that the influence of negative direct and positive indirect network effects offset each other. Conversely, we study contribution patterns in collaborative, complementary efforts. Moreover, we identify precisely how success breeds success in crowdsourced platform markets, which is commonly attributed to network effects (Biglaiser & Crémer, 2016; Eisenmann et al., 2006). If we understand network effects as increasing the participation by each contributor with growing platform size, our analysis contains subtle and nuanced insights about their role. We do find *some* evidence for direct network effects among contributors, but their impact on activity at the intensive margin is rather small. Instead, the size advantage we document mainly stems from the increased manpower at the extensive margin. As for indirect network effects, we cannot test relationships with increased wiki readership directly. However, we do find that HPCs are more active on better-maintained platforms, likely due to status- and impact-related motivation. This suggests that their expectation of greater viewership drives participation, consistent with indirect network effects. However, we only find this for a relatively small subset of core members, but not others. This adds nuance as it implies that the strength of indirect network effects is subject to heterogeneity. In addition, it also suggests that their strength is endogenous to contributor's effort provision: HPCs benefit from them precisely because they can attribute increased viewership to their effort provision.

Our study opens up several potential future research avenues. First, note that our research design generates results for the short-run only. Specifically, we investigate how contributors react to a workload (in the form of game updates) presented to them, conditional on the competitive position in that domain at that time. Future research could investigate precisely these potentially self-reinforcing dynamics between contributor activity and competition in the long run. Second, we observe the contributing side of our platforms, but not wiki readership. Hence, we (implicitly) assume that output created and readership are positively related. While we consider this assumption reasonable, future research could look at the interplay of both sides, which would also provide interesting insights about the relationship between direct and indirect network effects and its role for platform competition. Third, studying contribution dynamics in other settings like open source software development or bug-fixing platforms would help determine the scope of applicability of our findings. Finally, while we suggest acquisitions can be a suitable way to increase a platform's competitive position in crowdsourced markets, it is not clear how they affect contributor motivation. For instance, in the context of open-source software, being acquired by a commercial rival may hurt activity if it compromises motivations from trying to outcompete that rival. Hence, future research should study how this and related growth strategies relate to contributor motivation.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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